

Plant Leaf Disease Detection using Machine Learning

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Abstract: - India is a predominantly agricultural nation with a populace that relies on it to varying degrees (about 70%). The agricultural sector contributes to some of the national income. Farmers lose money due to a variety of agricultural illnesses, and large farmed areas make it difficult for cultivators to continuously monitor the crop. In the discipline of culture, algorithms for plant disease identification are crucial. In order to prevent the loss brought on by agricultural illnesses that severely influence crop quality and yield, quick and effective disease identification is crucial. With early detection and treatment, the mortality brought on by plant diseases and unneeded medication consumption can be decreased. Earlier, image processing was used to detect plant diseases on its own. Machine learning processes and image processing techniques are recommended for categorizing and identifying disorders. Crop diseases will be detected using a number of image processing stages, such as image capture, feature extraction from the raw image during pre-processing, disease prediction, feature classification, and fertilizer recommendation. It is essential to detect diseases since this will allow farmers to provide the best prevention measures. Classification, feature extraction, image processing, global image features, and machine learning are some related terms.

Key Words: - Classification, Feature Extraction, Image Processing, Global Image Features, Machine Learning.

I. INTRODUCTION

The harvest's quality, which is directly tied to plant development and yield, is what decides a farmer's capacity for company expansion. Different types of plant diseases affect the leaf, stem, seed, fruit, and other parts of the plant's anatomy in different ways. This problem seems to be better suited for machine learning. A number of machine learning algorithms have recently been presented for the categorization and detection of plant diseases using plant pictures. Numerous crops, most notably cash crops, are important for industrial and agricultural sectors of country.

Manuscript revised May 17, 2023; accepted May 18, 2023. Date of publication May 21, 2023.

This paper available online at <u>www.ijprse.com</u> ISSN (Online): 2582-7898; SJIF: 5.59

In India, six million farmers provide for their families directly. Research on leaf diseases has given rise to concepts in image processing such as image filtering, segmentation, and image feature extraction. Among the many available picture segmentation methods are Canny and Sobel segmentation, kmeans clustering, and Otsu thresholding. Several methods, including Support Vector Machine, Neural Network, and Homogeneous Pixel Counting, can be utilised for classification in the identification of cotton sickness. Features have recently started to matter in the classification process. Low accuracy and fewer photographs utilized to detect disease were two limitations of earlier proposed methods for illness identification. The plant leaves are mostly responsible for the illness. The research, which focuses on plan plant leader, finds that almost 91% of plant diseases affect the leaf of trees rather than the entire plant. The main diseases that damage leaves include insecticide (like tudtude, mawa), foliar leaf, fungus, and Alternaria leaf spot.

The application contains a variety of algorithms. Image processing makes it easier to separate picture shoots into object and background images. The identification of the features is an



important step in the study of the pictures. The study of image recognition is popular. Concepts from the field of plant leaf pattern recognition, which is used to detect diseases in the leaves, are applied in the pattern recognition discipline. Numerous strategies have been put forth over the last 20 years, but they have not yet been entirely resolved. But this is a challenging circumstance. A major issue is how to acquire stable and discriminative properties for categorization.

II. REVIEW OF LITERATURE

G. Saradhambal, Dhivya R., Latha S., Rajesh R. suggests the use of a CNN to identify plant diseases. Identification of the picture, which is a crucial tool for early disease diagnosis for growth in agricultural production, is one of the essential applications of image processing. The time and money spent on manual prediction will be reduced with the use of this technology. The author might infer from the aforementioned data that Convolution Neural Network (CNN) offers a remarkable degree of accuracy in disease detection. This work can be expanded upon to create a real-time programme that can identify additional plant species in addition to grapes. The system in use enlarges images, applies Gaussian filtering for image preprocessing to split the leaf area, and then employs CNN classification approach to identify the type of leaf illness. K. R. Aravind, Raja P., Mukesh K.V., Anirudh R., Ashiwin R. recommends that one of the active research areas that the classification of plant diseases using image processing requires more research in order to realize sustainable agriculture with suitable use of modern technologies. In this study, images of maize leaves from the Plant Village collection were used to identify the Cercosporin leaf spot, common rust, leaf blight, and healthy leaves. The recent emergence of the bag of features in the classification 6 problems has been investigated by evaluating the classification efficacy with multiclass support vector machines. The best average accuracy was reached using a number of features, scoring 83.7%. The effectiveness has also been compared to traits based on the co-occurrence of grey levels and to traditional histograms. The polynomial kernel function and the LS method for hyperplane generation were combined to produce the best average accuracy for the histogram-based features, which was 81.3%.

Ms. Kiran R. Gavhale, Prof. Ujjwala Gwande suggests it is implied that present. The paper analyses and summarizes image processing techniques used to detect plant diseases in a variety of plant species. SGDM, K-means clustering, BPNN, and SVM are the principal techniques for identifying plant diseases. These techniques are used to evaluate both healthy and diseased plants' leaves. The effect of background information on the final image, methodology optimizations for a specific plant leaf disease, and automation of the process for continual automated monitoring of plant leaf diseases in actual field settings are some of the challenges with these techniques. The analysis found that while this approach of disease detection has significant drawbacks, it shows great promise for detecting ailments in plant leaves. As a result, the existing research has potential for improvement. Pixel counting methods for RGB photographs are widely used in agriculture research. Image analysis can be used to identify plant illnesses in the fruit, stems, and leaves.

H Shima Ramesh Maniyath, Mr. Ramchandra Hebbar, Pooja R, Prasad Bhat N, Mr. P V Vinod, Nivedita M, Shashank N indicates that because it offers a quicker and more precise answer, the suggested approach is an upgrade over the one proposed in. The four key phases of the established processing scheme are as follows. After the segmentation phase, the next two phases are added one after the other. The first thing we do is find the pixels that are mostly green. Otsu's method is then used to mask these pixels, which are mostly green pixels, based on specific threshold values. As an additional step, the pixels with green, red, and blue values of zero and those on the boundaries of the infected cluster (object) were completely removed. The results of the experiment indicate that the suggested method is a reliable one for spotting diseases in plant leaves.

Shital Bankar, Amita Dube, Pranali Kadam, Prof. Sunil Deokule provides a method for automatically detecting plant disease that is accurate and effective. Both healthy and diseased plant leaf samples are subjected to the color feature extraction process. A method for locating plant disease is histogram matching. The cornerstones of histogram matching are the color feature and the edge detection technique. These examples are trained using two different approaches: layer separation, which separates layers of RGB images into red, green, and blue layers; and edge detection, which locates edges of layered images.

III. PROPOSED METHODOLOGY

A few of the stages in the process of identifying leaf illnesses include picture collection, preprocessing of images, extraction of features, and categorization of diseased leaves based on factors including color, shape, and texture. Getting the images is the first stage. Consider that e has just been uploaded utilizing leaf dataset's picture data. The picture is then produced using a number of methods.



In the third stage, features are extracted using the front portion of the picture of the ill leaf. Based on certain characteristics of the pixels or their texture, this is done. Following that, statistical analysis methods are used to categories the qualities that represent the provided image. Image feature comparison is done via machine learning. The categorization's results also reveal the leaf illness.

The suggested system has the following benefits:

- It consists of two feature extraction and classification algorithms that may successfully and reliably detect the disease in the image.
- The suggested approach has the ability to extract all spatial characteristics from a photo and can improve detection accuracy by utilizing deep learning.

3.1 Architecture Of Systems



Fig.1. Modified Architecture of Systems

3.2 Mathematical Model

The mathematical model for the Leaf Disease system is $asS = \{I, F, O\}$ Where,

I = Set of image leaf dataset F = Set of functions

O=leaf disease prediction $F = \{F1, F2, F3\}$

F1=Data Collection, F2=Data Preprocessing, F3=Feature Selection,

F4=Classification F5=Leaf disease detection

3.3 Algorithms

3.3.1 Convolution neural network algorithm (CNN):

Two layers make up CNN algorithm. The initial layer is called the feature extraction layer, where local ready fields are directly tied to the input of each neuron and local features are gathered. After being obtained, the local features' spatial relationship with other features will be displayed. The feature map layer, which consists of a plane with a predetermined number of neurons on each, is the other layer. The sigmoid function is utilized by the highlighted plan structure. This function, also referred to as CNN's activation function, alters the feature map at will. After the computational layer is applied, the local average and second extract are calculated using each convolution layer in the CNN. This specific structure reduces resolution by extracting two features.

- Choose the dataset.
- Utilize information gain and ranking to carry out feature selection.
- Use CNN's classification algorithm
- Do each Feature function value calculation for the input layer.
- Calculate each feature's bias class.
- Once created, the feature map is added to the forward pass input layer.
- Convolution cores for a feature pattern should be calculated.
- Create the feature value and subsample layer.
- The output layer's kth neuron's input deviation is backpropagated.
- Lastly, present the results of the categorization using the chosen feature.

3.4 Discussion and Result



Fig.2. Convolution Neural Network

The section exhibits the general accuracy of the CNN classification approach. As a result, this strategy predicts leaf disease better than the present one.

Table No.1. of the Classification Accuracy Graph (Method Comparison)

	Existing System	Proposed System (CNN)
Precision	61.6	50.70
Recall	74.1	87.64
F-Measure	69.8	77.31
Accuracy	79.29	92.26

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IV. CONCLUSION

The study of the various illnesses that affect leaves can be used to identify them early on before they harm the entire plant, which is how disease analysis is carried out in this case for the identification of leaf diseases. Here's a method to assist you in finding the illness more rapidly. Thanks to meteorological information and image processing, we can claim with certainty that we can maintain a high level of output by avoiding the various illnesses that are present on the plant's leaves. The system's performance has been improved, resulting in better outcomes thanks to the implementation of feature extraction and classification algorithms.

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